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Individual Trend Inflation[*]

Toshitaka Sekine[†], Frank Packer[‡], and Shunichi Yoneyama[§]

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Abstract

This paper extends the recent approaches to estimate trend inflation from the survey responses of individual forecasters. It relies on a noisy information model to estimate the trend inflation of individual forecasters. Applying the model to the recent Japanese data, it reveals that the added noise term plays a crucial role and there exists considerable heterogeneity among individual trend inflation forecasts that drives the dynamics of the mean trend inflation forecasts. Divergences in forecasts as well as moves in estimates of trend inflation are largely driven by a identifiable group of forecasters who see less noise in the inflationary process, expect the impact of transitory inflationary shocks to wane more quickly, and are more flexible in adjusting their forecasts of trend inflation in response to new information.

JEL Classification Number: E31, E52, E58

Keywords: inflation forecast, disagreement, unobserved components model, noisy information, inflation target, quantitative and qualitative monetary easing, Bank of Japan

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1 Introduction

There is no doubt that trend inflation, embedded in actual data of consumer prices and in inflation expectations of various economic players, is one of the most important variables for the conduct of monetary policy. For this reason, huge effort has been made by a number of researchers to extract trend inflation. In this paper, we try to contribute to this literature by extending the existing studies in the following two ways.

First, we incorporate a noisy information model more explicitly in an unobserved components model. An unobserved components model such as Beveridge and Nelson (1981) is a useful tool to decompose actual data into its trend and transitory components. Stock and Watson (2007, 2016) apply the procedure to estimate trend inflation by incorporating stochastic volatility in the model. Kozicki and Tinsley (2012) use an unobserved components model to analyze inflation forecasts. Other research papers, many of them more recent, have extracted trend inflation from actual and forecast inflation rates (Chan et al. (2018), Nason and Smith (2021), Patton and Timmermann (2010) and Yoneyama (2021)).

In doing so, we add one extra disturbance term, which can be interpreted to represent a noise signal of Woodford (2003). Thus, our research is also related with long literature of information rigidity developed by Mankiw and Reis (2002), Mankiw et al. (2004) and Coibion and Gorodnichenko (2012, 2015). Shintani and Ueda (2021) have broken down noisy information models between Lucas and Woodfordian variants, whereby the former assumes that forecasters can observe the true state of realised inflation (including its trend and transitory components) at the end of each period, while the latter assumes that realisations are never revealed. Our model can be seen as Woodfordian.

Second, we apply the model to individual forecasts to extract *individual* trend inflation. The above-cited studies utilize the average of individual inflation forecasts to derive trend inflation. However, one of the important lessons coming from the information rigidity literature is the importance of heterogeneity in forming inflation expectations. For this reason, it can be valuable for us to work with individual responses to the survey when incorporating information rigidity into our model. In the Japanese context, assuming specific models of the term structures of inflationary expectations, Hattori and Yetman (2017) and Shintani and Soma (2020) derive long-run inflation expectations of individual forecasters. However, they do not analyze the heterogeneity of individual responses, including the degree of disagreement of inflation forecasts discussed in this paper's later sections.

In order to demonstrate the utility of our approach, we apply it to recent Japanese data to shed light on the impact of introducing an explicit inflation target policy and various unconventional measures of monetary easing. The Bank of Japan (BOJ) adopted a 2 percent inflation target in January 2013, which was followed by a series of monetary easing measures. These include the Quantitative and Qualitative Monetary Easing (QQE) program in April 2013, the Negative Interest Rates Policy (NIRP) in January 2016 and the Yield Curve Control (YCC) of 10 year Japanese Government Bonds (JGB) in September 2016.

Thus, our paper relates to numerous studies investigating the effects of inflation targeting policy as well as unconventional monetary easing, such as Hayashi and Koeda (2019), Christensen and Spiegel (2019), Miyao and Okimoto (2017), Ehrmann (2015), Honda et al. (2013), Ehrmann et al. (2012), Ueda (2012), and Capistran and Ramos-Francia (2010). In addition, Hattori et al. (2021), de Mendonca and de Deus (2019), Hubert (2015), and Pederson (2015) discuss the effectiveness of central bank communications and own forecasts through their impact on private inflation forecasts.

To briefly preview our results, we first work with the mean of inflation forecasts, and show that the added noise term improves the fit of the model dramatically. Trend inflation obtained from the average inflation forecasts surged after the introduction of the 2% inflation target and the QQE in 2013 and again after the adoption of the YCC in 2016. We then estimate individual trend inflation rates and document considerable heterogeneity among the forecasters. Based on a cluster analysis of estimated parameter variables, we divide forecasters in two groups and find that forecasters who see smaller noise in actual inflation also tend to think the effects of cyclical components of inflation will wane more quickly and are more likely to raise their assessment of trend inflation. In fact, such forecasters were mostly responsible for the surge in average trend inflation observed earlier, and also for the wider disagreement in trend inflation observed in tandem. The adoption of the inflation target and subsequent unconventional monetary policy measures succeeded in raising the trend inflation estimates of some forecasters but not all.

The rest of the paper will proceed as follows. In the next section, we introduce our model of noisy information as an extension of an unobserved components model. In section 3, we describe the survey data from which we extract trend inflation. In section 4, after explaining how to bridge the survey observations to the earlier noisy information model, we present our main estimation results. In section 5, we interpret our findings and discuss the policy implications of our results in the light of the aggressive monetary policy efforts made by the Bank of Japan starting in 2013 to lift inflation. Section 6 concludes the paper.

2 Model

We use the following noisy information model in order to retrieve trend inflation of individual forecasters.

$$\pi_t = \tau_{i,t} + c_{i,t} + \epsilon_{i,t},\ \epsilon_{i,t} \sim N(0, \sigma^2_{\epsilon i,t}) \tag{1}$$

$$\tau_{i,t} = \tau_{i,t-1} + \nu_{i,t},\ \nu_{i,t} \sim N(0, \sigma^2_{\nu i}) \tag{2}$$

$$c_{i,t} = \rho_i c_{i,t-1} + \omega_{i,t},\ \omega_{i,t} \sim N(0, \sigma^2_{\omega i}) \tag{3}$$

where π_t is the latest actual inflation rate available when forecaster i makes her inflation forecasts at time t. She decomposes observed inflation into permanent trend $\tau_{i,t}$, transitory $c_{i,t}$ and noise $\epsilon_{i,t}$ components according to her interpretation of observations (equation (1)). She assumes that trend and transitory components follow stochastic processes specified by equations (2) and (3).

Our model can be seen as an extension of an unobserved components model in a noisy information setup. Instead of equation (1), a conventional unobserved components model such as Stock and Watson (2007, 2016) uses

$$\pi_t \equiv \tau_t + c_t.$$

Analysing individual forecasts, we add $\epsilon_{i,t}$, the presence of which can be justified by a noisy signal of Woodford (2003). We assume stochastic volatility for this term to allow serial correlation of its variance — once forecasters perceive the data is noisy, the situation may continue for a while.

$$\sigma^2_{\epsilon i,t} = \gamma_i \exp(\lambda_{i,t}) \tag{4}$$

$$\lambda_{i,t} = \theta_i \lambda_{i,t-1} + \eta_{i,t}, \ \ \eta_{i,t} \sim N(0, \sigma^2_{\eta i}). \tag{5}$$

Based on this setup, forecaster i formulates her k-period ahead projection $\hat{\pi}_{i,t,+k}$ at the time of t as

$$\hat{\pi}_{i,t,+k} = \tau_{i,t} + \rho_i^k c_{i,t} + u_{i,t,+k}, \ \ u_{i,t,+k} \sim N(0, \sigma^2_{ui,+k}) \tag{6}$$

where $u_{i,t,+k}$ is a measurement error. Provided $|\rho_i| < 1$, inflation projection converges to the trend inflation as $\hat{\pi}_{i,t,+\infty} = \tau_{i,t}$.

Equations (1) – (3) and (6) can be compactly summarized in a state-space form where the observation equation is

$$\begin{bmatrix} \pi_t \\ \hat{\pi}_{i,t,+1} \\ \vdots \\ \hat{\pi}_{i,t,+k} \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \tau_{i,t} + \begin{bmatrix} 1 \\ \rho_i \\ \vdots \\ \rho_i^k \end{bmatrix} c_{i,t} + \begin{bmatrix} \epsilon_{i,t} \\ u_{i,t,+1} \\ \vdots \\ u_{i,t,+k} \end{bmatrix}, \tag{7}$$

and the transition equation is

$$\begin{bmatrix} \tau_{i,t} \\ c_{i,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & \rho_i \end{bmatrix} \begin{bmatrix} \tau_{i,t-1} \\ c_{i,t-1} \end{bmatrix} + \begin{bmatrix} \nu_{i,t} \\ \omega_{i,t} \end{bmatrix}. \tag{8}$$

3 Data

3.1 ESP Survey

For inflation forecasts, we take those from the ESP Survey from 2004M4 to 2020M3. The ESP Survey is a survey of professional forecasters in Japan conducted by the Japan Center for Economic Research (JCER). Each month, the JCER collects predictions from around 40 forecasters regarding various macroeconomic indicators (such as GDP and its components) as well as financial variables (such as 10-year JGB yields, exchange rates, money growth, etc.). In this study, we will focus on core Consumer Price Index (CPI) inflation (excluding fresh food).

These professional forecasters are identified with an institution code with which those forecasters are affiliated. Hence, strictly speaking, different persons may have submitted their forecasts with the same ID, if there is a change in personnel in these institutions. The JCER does not disclose names of forecasters nor their characteristics (age, gender, job experience, etc.). The only information we have is the type of institutions such that these institutions are associated with banks, insurance companies, securities firms and others.[1]

Each month, the JCER surveys quarterly and annual (fiscal year) forecasts.[2] We use $\hat{\pi}^q_{t,+0}, ..., \hat{\pi}^q_{t,+4}$ (nowcast to 4-quarter ahead inflation) and $\hat{\pi}^a_{t,+1}$ (inflation in the next fiscal year), where $\hat{\pi}^q_{t,+k}$ is a forecast of quarterly average year-on-year core CPI inflation for k quarters ahead and $\hat{\pi}^a_{t,+k}$ is its annual average for k years ahead. Depending on the survey timing, the JCER asks for inflation in the longer horizon like $\hat{\pi}^q_{t,+5}, ..., \hat{\pi}^q_{t,+8}$ and $\hat{\pi}^a_{t,+2}$, but we do not incorporate them in our estimation because they are not available consistently through the sample period.

The JCER surveys core CPI inflation forecasts with and without the direct effects of consumption tax hikes.[3] We use ones excluding consumption tax effects because we are primarily interested in the impacts of monetary policy on ESP inflation forecasts. Before the JCER began to survey without-consumption-tax-effect forecasts in 2013M10, we subtract 2% points from core CPI inflation forecasts (including consumption tax effects) for FY2014 (for 2012M10-2013M9 surveys) and the corresponding quarters (for 2013M1-2013M9 surveys).[4] In its October 2012 Outlook, the Bank of Japan disclosed that it expected core CPI inflation would increase by 2 percentage points for the 2014 consumption tax hike. That impact seemed to become common knowledge across ESP forecasters, if we look at the difference between with- and without-consumption-tax-effect forecasts from 2013M10.

[1] Japanese securities firms partly correspond to US broker dealers and partly US investment banks (Ito and Hoshi (2020), p.114).

[2] Japanese fiscal year is from April to March of the following calendar year.

[3] During the sample period, consumption tax was raised from 5% to 8% on April 1, 2014 and 8% to 10% on October 1, 2019. The second consumption tax was originally scheduled on October 1, 2015, but in November 2014, Prime Minister Abe announced to defer it to April 1, 2017. In June 2016, he decided again to defer it to October 1, 2019.

[4] One forecaster (ID206) failed to submit the without-consumption-tax-effect forecasts in 2014M4 and 2014M5. We fill these missing observations by applying the same 2 percentage points correction to his/her with-consumption-tax-effect forecasts. We also made adjustments for responses of ID205 in 2013M10 and 2013M11 so that quarterly and annual figures become consistent each other.

On a few occasions (corresponding to about 2% of 7,425 sample records), some forecasters fail to submit their forecasts for a month or so. In the following estimation, we assume that the forecasters maintained their latent variables $\tau_{i,t}$, $c_{i,t}$ and $\lambda_{i,t}$ at the same levels during their absence from the survey. As a robustness check, we restricted the samples to the forecasters who reported for more than 36 months consecutively (the sample records are then reduced to 5,617) and treated the forecasters as different entities before and after the interruption. The results did not change materially (they are available on request).

3.2 Actual CPI

For actual CPI, we use a month-to-month change in seasonally adjusted core CPI (excluding fresh food).

$$\pi_t = \frac{P_t}{P_{t-1}} - 1 \approx p_t - p_{t-1} = \Delta p_t,$$

where P_t is CPI at time t and the lower letter denotes its logarithm.

The actual CPI that we use for the analysis should be real time data so as to faithfully mimic the information set available to the forecasters at the time. This implies that at the time of the rebasing of the CPI, that takes place every five years, we should use then officially published seasonally adjusted series before the release of new series and switch to the new one thereafter.[5] For instance, when the the Statistics Bureau of Japan changed the base year from 2000 to 2005 in August 2006, we use the 2000 year based CPI series up to July 2006 and switch to the 2005-index series from August 2006.

In order to exclude the direct effects of the consumption tax hikes, 2 percentage points are subtracted from π_{2014M4}, which is consistent with the adjustment made for the ESP forecasts mentioned above. In addition, 0.2 percentage points are subtracted from $\pi_{2019M10}$, the effect of which was published by the Statistics Bureau of Japan and also is consistent with what ESP forecasters embedded in their forecasts.

[5] Every five years, the Statistics Bureau of Japan switches the base years for the CPI calculation. At that time, it changes the weight and the coverage of CPI baskets as well as compilation details such as quality adjustments. These changes have sometimes resulted in significant revisions.

4 Estimation

4.1 State-Space Representation

As we use the ESP forecasts of annual changes in the quarterly and the annual average CPI (π_t^q and π_t^a), we need to modify the above introduced observation equation (7) accordingly.

These inflation rates can be expressed by the month-to-month inflation π_t as:

$$
\begin{aligned}
\pi_t^q &= \frac{P_t + P_{t-1} + P_{t-2}}{P_{t-12} + P_{t-13} + P_{t-14}} - 1 \\
&\approx \frac{1}{3}(\pi_t + 2\pi_{t-1} + 3\pi_{t-2} + \cdots + 3\pi_{t-11} + 2\pi_{t-12} + \pi_{t-13}) = \mathcal{S}^q \begin{bmatrix} \pi_{t-13} & \cdots & \pi_t \end{bmatrix}', \\
\pi_t^a &= \frac{P_t + \ldots + P_{t-11}}{P_{t-12} + \ldots + P_{t-23}} - 1 \\
&\approx \frac{1}{12}(\pi_t + 2\pi_{t-1} + \cdots + 12\pi_{t-11} + \cdots + 2\pi_{t-21} + \pi_{t-22}) = \mathcal{S}^a \begin{bmatrix} \pi_{t-22} & \cdots & \pi_t \end{bmatrix}',
\end{aligned}
$$

where $\mathcal{S}^q = \begin{bmatrix} \frac{1}{3} & \frac{2}{3} & \frac{3}{3} & \cdots & \frac{3}{3} & \frac{2}{3} & \frac{1}{3} \end{bmatrix}$ and $\mathcal{S}^a = \begin{bmatrix} \frac{1}{12} & \frac{2}{12} & \cdots & \frac{12}{12} & \cdots & \frac{2}{12} & \frac{1}{12} \end{bmatrix}$.

Then, $\hat{\pi}_{i,t,+0}^q, \ldots, \hat{\pi}_{i,t,+4}^q$ and $\hat{\pi}_{i,t,+1}^a$ can be expressed as

$$
\begin{bmatrix} \hat{\pi}_{i,t,+0}^q \\ \vdots \\ \hat{\pi}_{i,t,+4}^q \\ \hat{\pi}_{i,t,+1}^a \end{bmatrix} = \mathcal{S} \begin{bmatrix} \pi_{t-12} \\ \vdots \\ \pi_t \\ \hat{\pi}_{i,t,+1} \\ \vdots \\ \hat{\pi}_{i,t,+23} \end{bmatrix} = [\mathcal{S}_1 | \mathcal{S}_2] \begin{bmatrix} \pi_{t-12} \\ \vdots \\ \pi_t \\ \hat{\pi}_{i,t,+1} \\ \vdots \\ \hat{\pi}_{i,t,+23} \end{bmatrix} = \mathcal{S}_1 \begin{bmatrix} \pi_{t-12} \\ \vdots \\ \pi_t \end{bmatrix} + \mathcal{S}_2 \begin{bmatrix} \hat{\pi}_{i,t,+1} \\ \vdots \\ \hat{\pi}_{i,t,+23} \end{bmatrix}, \qquad (9)
$$

where $\mathcal{S}$ is a 6×36 selection matrix, an element of which consists of $\mathcal{S}^q$ and $\mathcal{S}^a$ (the exact form differs according to the survey month — see Appendix for more details). This can be usefully divided into a 6×13 matrix $\mathcal{S}_1$ and a 6×23 matrix $\mathcal{S}_2$, where the former corresponds to actual CPI ($\pi_{t-12}, \ldots, \pi_t$), and the latter corresponds to its projections ($\hat{\pi}_{i,t,+1}, \ldots, \hat{\pi}_{i,t,+23}$).

Substituting equation (6) into equation (9), we have the new observation equation mapped to the ESP forecasts as

$$\begin{bmatrix} \pi_t \\ \hat{\pi}^q_{i,t,+0} \\ \vdots \\ \hat{\pi}^q_{i,t,+4} \\ \hat{\pi}^a_{i,t,+1} \end{bmatrix} = \begin{bmatrix} 0 \\ \mathcal{B} \end{bmatrix} + \begin{bmatrix} 1 & 1 \\ \mathcal{Z}_\tau & \mathcal{Z}_c \end{bmatrix} \begin{bmatrix} \tau_{i,t} \\ c_{i,t} \end{bmatrix} + \begin{bmatrix} \epsilon_{i,t} \\ u^q_{i,t,+0} \\ \vdots \\ u^q_{i,t,+4} \\ u^a_{i,t,+1} \end{bmatrix},$$

where

$$\mathcal{B} = \mathcal{S}_1 \begin{bmatrix} \pi_{t-12} \\ \vdots \\ \pi_t \end{bmatrix}, \; \mathcal{Z}_\tau = \mathcal{S}_2 \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \text{ and } \mathcal{Z}_c = \mathcal{S}_2 \begin{bmatrix} \rho_i \\ \vdots \\ \rho_i^{23} \end{bmatrix}.$$

Transition equation does not change from equation (8).

$$\begin{bmatrix} \tau_{i,t} \\ c_{i,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & \rho_i \end{bmatrix} \begin{bmatrix} \tau_{i,t-1} \\ c_{i,t-1} \end{bmatrix} + \begin{bmatrix} \nu_{i,t} \\ \omega_{i,t} \end{bmatrix}.$$

4.2 Estimation Results

We estimate the above state-space form by a Bayesian Markov chain Monte Carlo (MCMC), which exploits an efficient Gaussian smoother developed by De Jong and Shephard (1995). For stochastic volatility, we follow Nakajima (2011) who uses the multi-move sampler of Shephard and Pitt (1997) modified by Watanabe and Omori (2004).[6] That is, for each individual forecasters (62 in total), we run the Gibbs sampler for 21,000 replications, with 1,000 burn-in replications discarded and 20,000 replications retained. On top of that, we repeat the same exercise for the average of ESP forecasts, $\hat{\pi}^q_{*,t,+k} = \sum_i \hat{\pi}^q_{i,t,+k}/N_t$ and $\hat{\pi}^a_{*,t,+k} = \sum_i \hat{\pi}^a_{i,t,+k}/N_t$ (N_t is the number of forecasters), treating a mean forecaster (denoted by $*$) as an additional individual.

Table 1: Log Marginal Likelihood Estimates

Baseline Model: equations (1) to (6)	-28.491
Alternative Models:	
Drop a noise term $\epsilon_{i,t}$ from equation (1)	-66.506
Use only $\hat{\pi}_{i,t,+1}$ in equation (6)	-33.165
Assume stochastic volatility of $\nu_{i,t}$ and $\omega_{i,t}$ in equations (2) and (3)	-33.971

Note: $\hat{\pi}_{i,t,+1}$ in equation (6) corresponds to $\hat{\pi}^q_{i,t,+0}$ in equation (9).

4.2.1 Mean Forecasts

Before going to the analyses of individual trend inflation, we examine how our model behaves with mean inflation forecasts. Table 1 provides marginal likelihood of our baseline model and its alternatives. Following Chan et al. (2018), we calculate the marginal likelihood based on the predictive likelihood in terms of actual inflation over the last 36-month period (2017M4-2020M3). The smaller negative values indicate the better fit of the model. That is, the baseline model shows the best performance compared with the alternatives.

More specifically, comparison with each alternative is as follows. First, dropping a noise term $\epsilon_{i,t}$ from equation (1) drastically deteriorates the fit. This clearly indicates how crucial our assumption of noisy information is. The second alternative sees the role of longer-term inflation forecasts. As stated above, we add nowcast to 4-quarter ahead inflation forecasts $(\hat{\pi}^q_{i,t,+0}, \ldots, \hat{\pi}^q_{i,t,+4})$ and that of the next fiscal year $(\hat{\pi}^a_{i,t,+1})$ in the observation equations corresponding to equation (6). Restricting information just to nowcast $\hat{\pi}^q_{i,t,+0}$ worsens the marginal likelihood compared to the baseline. The third alternative mimics Stock and Watson (2007, 2016) by assuming stochastic volatility of $\nu_{i,t}$ and $\omega_{i,t}$ in the transition equations (2) and (3). This also leads to deterioration in the marginal likelihood compared to the baseline.

Table 2 summarizes posterior mean and standard deviation of parameters obtained from the average of sample forecasters. AR coefficients for the transitory component $(c_{*,t})$ and stochastic volatility $(\lambda *,_t)$ are 0.887 and 0.933 respectively and show high persistence of these components. In terms of trend inflation, $\sigma_{\nu,*}$ is a key parameter that determines how smoothness the series is. 0.015% is more or less equivalent to standard deviation of the Hodrick-Prescott (HP) filtered π_t (0.030%), that is, the obtained trend inflation indicated below is as smooth as the HP-filtered

[6] All the codes are written in Ox (Doornik (2007)), otherwise noted. We leave details of the algorithm to the accompanied online appendix [not attached].

Table 2: Posteriors for Mean Forecaster

	Mean	Standard Deviation	Geweke's CD
ρ_* (AR of $c_{*,t}$)	0.887	0.039	0.37
$\sigma_{u*,+0q}$ ($\hat{\pi}^q_{*,t,+0}$)	0.205	0.011	0.43
$\sigma_{u*,+1q}$ ($\hat{\pi}^q_{*,t,+1}$)	0.204	0.011	-0.03
$\sigma_{u*,+2q}$ ($\hat{\pi}^q_{*,t,+2}$)	0.159	0.009	-0.55
$\sigma_{u*,+3q}$ ($\hat{\pi}^q_{*,t,+3}$)	0.112	0.007	0.34
$\sigma_{u*,+4q}$ ($\hat{\pi}^q_{*,t,+4}$)	0.116	0.008	-0.60
$\sigma_{u*,+1a}$ ($\hat{\pi}^a_{*,t,+1}$)	0.110	0.007	0.49
$\sigma_{\nu,*}$ ($\tau_{*,t}$)	0.015	0.001	-0.62
$\sigma_{\omega,*}$ ($c_{*,t}$)	0.018	0.002	-0.32
θ_* (AR of $\lambda*_{,t}$)	0.933	0.046	0.48
$\sigma_{\eta*}$ (SV)	0.274	0.108	0.12
γ_* (SV)	0.018	0.008	-1.09

Note: Geweke's CD is Geweke's Convergence Diagnostic which follows $N(0, 1)$.

trend.[7]

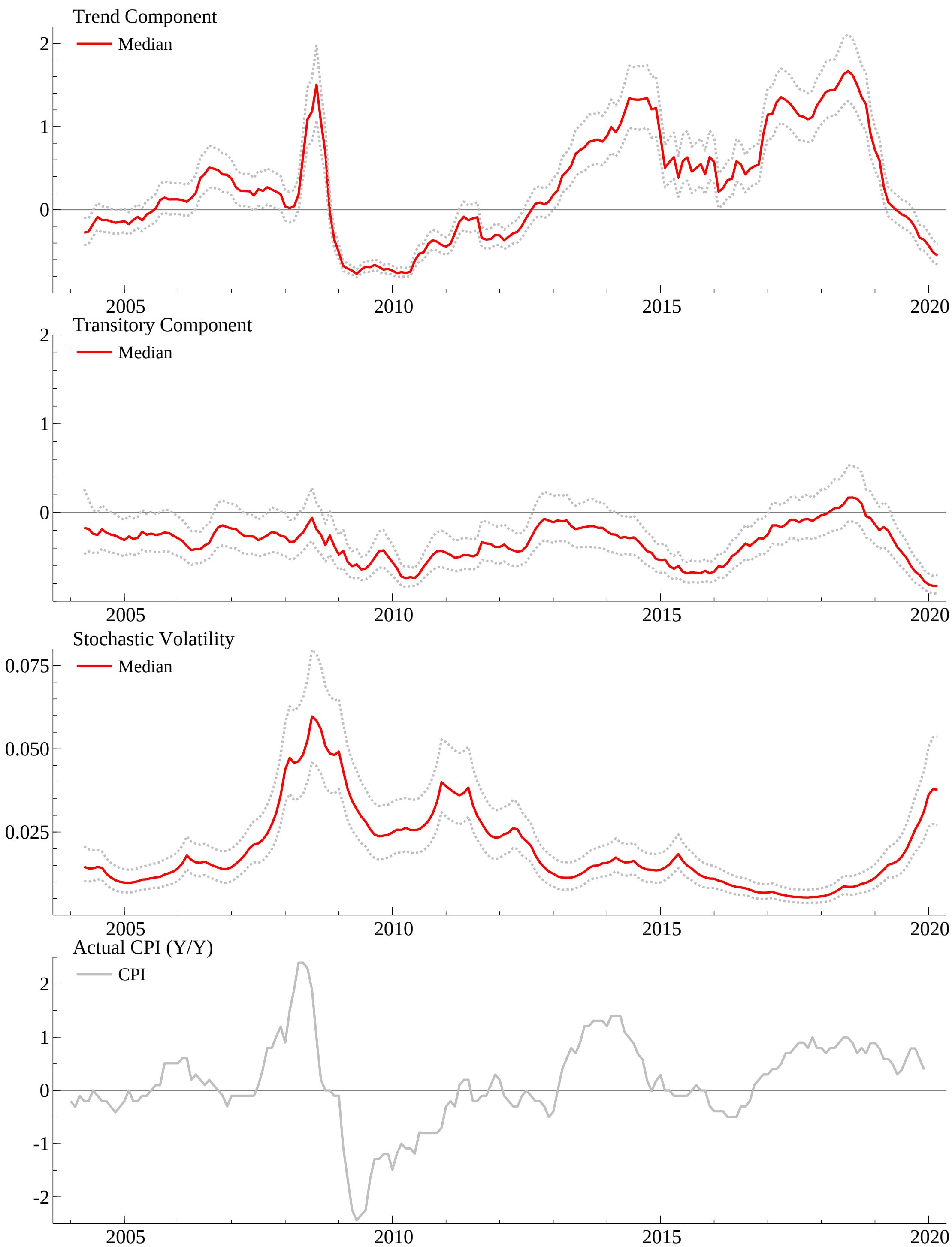
Figure 1 shows thus obtained posterior medians of trend/transitory components as well as stochastic volatility (red solid lines) together with their 80% ranges (gray dotted lines). There are several interesting observations.

First, the trend component ($\tau_{*,t}$) increased markedly after the introduction of the 2% inflation target in 2013M1 and the quantitative and qualitative monetary easing in 2013M4 (the first panel). It reached 1.3% in 2014M10 and after some easing in between, 1.7% in 2018M7. This trend component also increased in 2008 before the Great Financial Crisis (GFC) hit Japan's economy. It is interesting to observe these three hikes in trend inflation do not reflect the order of actual inflation: although the elevation of actual inflation is more distinctive in 2008 compared with 2018 (and somewhere in between in 2014), trend inflation is higher in 2018 than those in the first two hikes.

Second, transitory component ($c_{*,t}$) hoovered small negative during most of the sample period (the second panel). This can be interpreted that ESP forecasters tend to think actual inflation was pushed down by a transitory effect and anticipate that effect would diminish gradually going forward. This implies that, as long as trend inflation is positive, inflation forecasts become higher

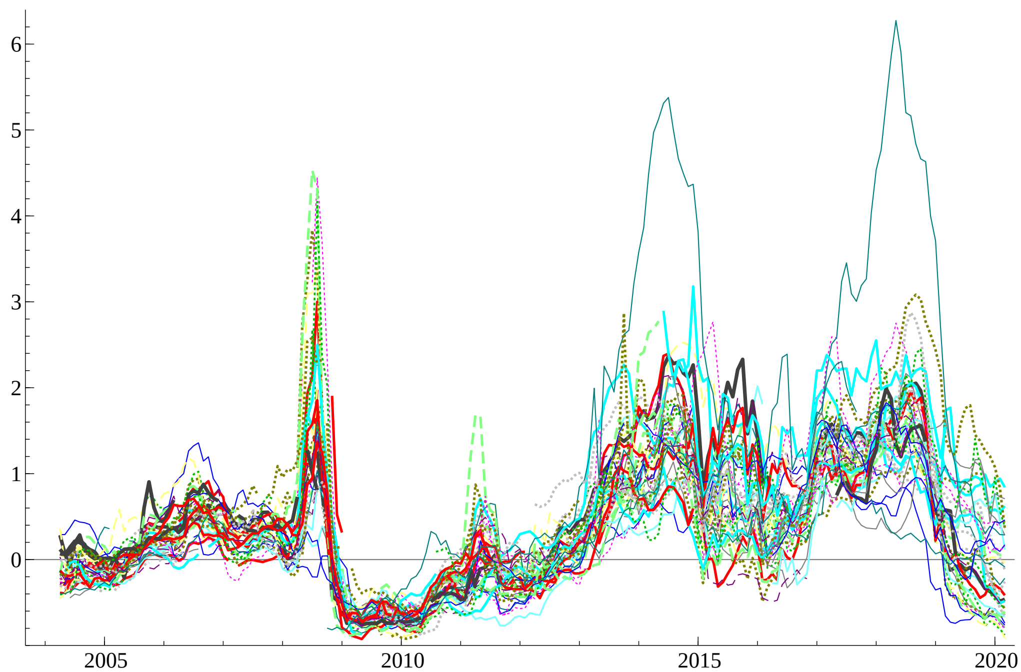
[7] We use a Gamma prior which assumes a prior for $\sigma_{\nu,*}$ is 0.1%. This is slightly lower than the actual standard deviation of π_t during the sample period (0.14%).

Figure 1: Estimates Using Mean Forecasts



Note: Posterior medians and 80% ranges (gray dotted lines) derived from mean forecasts. Trend and transitory components are expressed in annualized percent (the same, hereafter). Actual CPI is year-on-year real-time core CPI (excluding fresh food) released from the Statistical Bureau of Japan. The direct effects of raising consumption tax are excluded.

Figure 2: Individual Trend Inflation



Note: Posterior mean of trend components of individual forecasts.

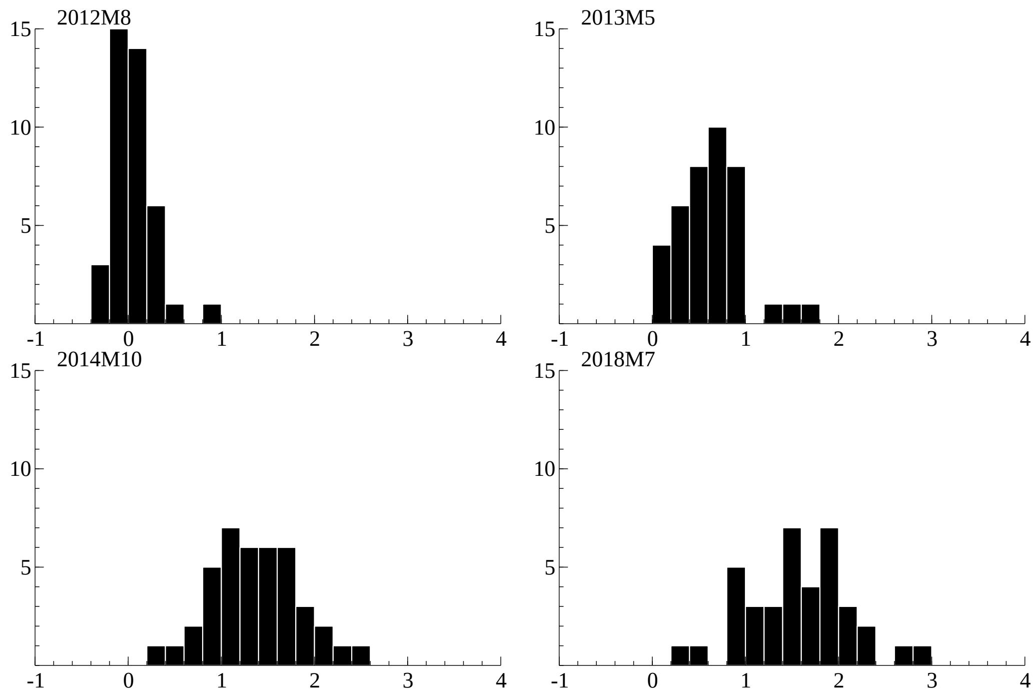
in the longer time horizon (and converge to the trend inflation level). In an analogy of a yield curve, an inflation forecast curve, drawn on the plane with the forecast inflation rate on the vertical axis and forecast horizon on the horizontal axis, has a positive slope in most of time.

Third, the noise ($\epsilon_{*,t}$ in our noisy information model of equation (1)) plays an indispensable role as its stochastic volatility is significant thorough the sample. The volatility increases during 2008-2009, when actual inflation showed a large up and down due to commodity prices developments and the GFC (the third and the fourth panels). Since then, the volatility had gradually declined even though actual inflation rose after 2013. It shot up toward the end of sample period, but this may be subject to the end-of-period problem of smoothing.

4.2.2 Individual Forecasts

Figure 2 displays all posterior means of trend components of individual forecasters ($\tau_{i,t}$). In a very broad view, these individual trend inflation rates move together—a surge in 2008, a rise after 2013 and another rise from 2017, but a more closer look highlights considerable heterogeneity

Figure 3: Histogram of Individual Trend Inflation



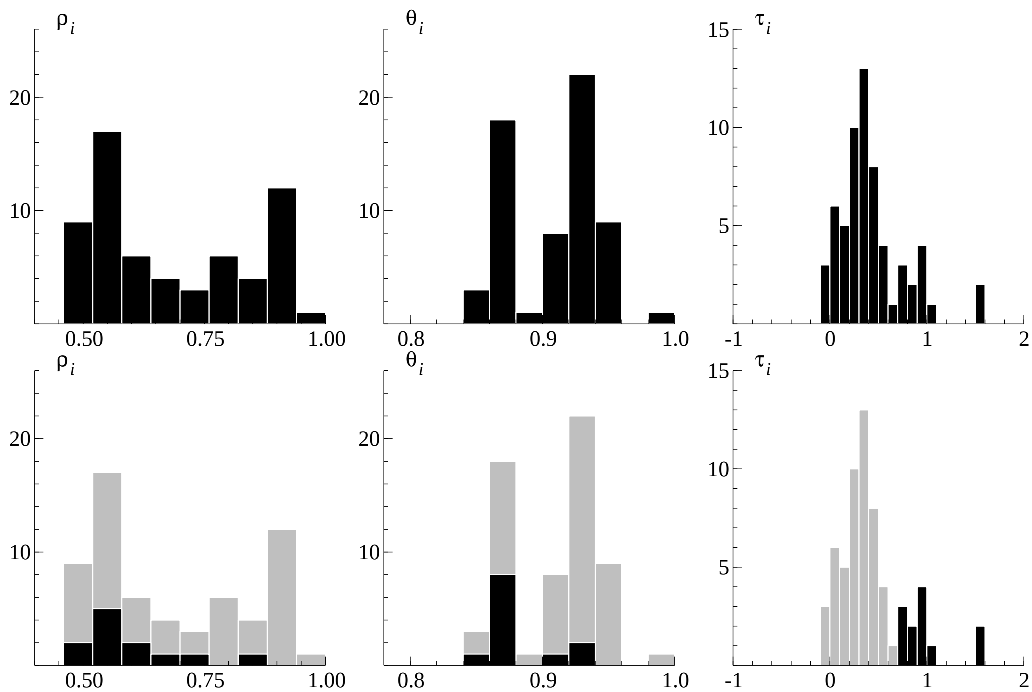
or divergence among them.

That heterogeneity becomes more visible in their cross-sectional distributions. In Figure 3, we plot histograms at four data points. The first one is 2012M8 well before the launch of Abenomics (the upper left panel);[8] the second one is 2013M5 just after the introduction of the quantitative and qualitative monetary easing (the upper right panel); and the third and the fourth ones are 2014M10 and 2018M7 (two bottom panels), which corresponds to the recent peaks of trend inflation in Figure 1. There is an apparent shift in the distributions to the right: the mode was below zero percent in 2012M8: it turned into the positive territory in 2013M5 to reach slightly below 1 percent in 2014M5 and close to 2 percent in 2018M7. At the same time, the heights of these modes lowered and the tails became more widely spread.

The heterogeneity is also clear in estimated parameters. The upper-left and the upper-center panels in Figure 4 are the histograms of estimated ρ_i and θ_i, which are AR coefficients of individual transitory component $c_{i,t}$ and stochastic volatility of noise term $\lambda_{i,t}$. The upper-right

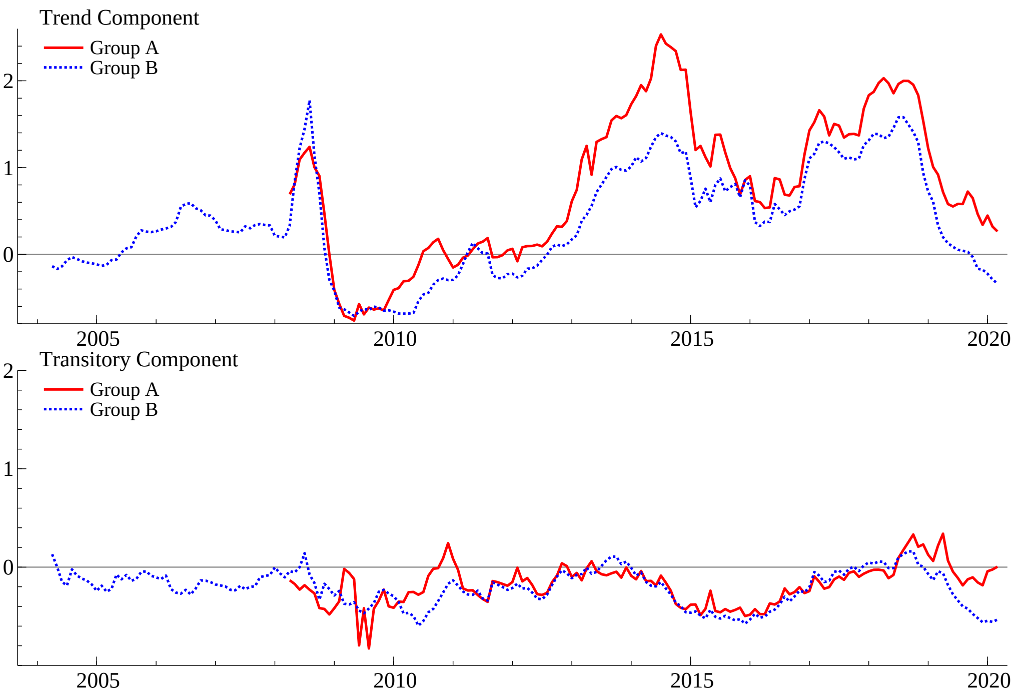
[8] Abenomics refers to the economic policies introduced by Shinzo Abe, who served his second term of Prime Minister from 2012M12 to 2020M8.

Figure 4: Histogram of Estimated Parameters



Note: The upper panels are histogram of estimated parameters ρ_i, θ_i and the historical mean of individual trend inflation $\tau_i = \frac{1}{T}\sum_t^T \tau_{i,t}$. The black and the grey parts of the histograms in the lower panels are that constructed from Group A and B identified by the cluster algorithm.

Figure 5: Trend and Transitory Components



panel is the histogram of the historical means of individual trend inflation, $\tau_i = \frac{1}{T}\sum_t^T \tau_{i,t}$. Their bi-modal shapes seem to indicate that these histograms are sampled from the mixture of two distributions, that is, there are two types of forecasters whose characteristics are captured by each distribution.

We segment 62 sample forecasters into two groups, Groups A and B, by applying the K-means clustering algorithm to these three parameter variables.[9] These two groups correspond to the black and the grey parts of the histograms in the lower panel of Figure 4. The algorithm identifies 12 forecasters as Group A whose trend inflation τ_i is high. Indeed, Group A forecasters have persistently higher trend inflation than Group B forecasters, which is not for the case with transitory components (Figure 5). At the same time, the figures show that Group A forecasters entered the survey during the sample period: this is the reason why the red solid lines of Group A started in 2008.

The lower panels of Figure 4 also suggest that Group A tend to be the lower side of distributions of ρ_i and θ_i. Comparison of posterior means of parameters between Groups A and B in

[9]We use the `sklearn.cluster.KMeans` class of Python.

Table 3: Posteriors for Groups A and B

	Group A	Group B	t-value	q-value
ρ_i	0.589	0.708	-2.821	0.003
$\sigma_{u,i,+0q}$	0.294	0.285	0.379	0.353
$\sigma_{u,i,+1q}$	0.289	0.283	0.252	0.401
$\sigma_{u,i,+2q}$	0.247	0.236	0.606	0.273
$\sigma_{u,i,+3q}$	0.217	0.187	1.371	0.088
$\sigma_{u,i,+4q}$	0.249	0.220	1.301	0.099
$\sigma_{u,i,+a}$	0.207	0.181	1.339	0.093
$\sigma_{\nu,i}$	0.025	0.023	0.668	0.253
$\sigma_{\omega,i}$	0.026	0.026	-0.114	0.455
θ_i	0.882	0.916	-3.182	0.001
$\sigma_{\eta,i}$	0.145	0.251	-5.429	0.000
γ_i	0.010	0.015	-3.180	0.001

Note: t-value and q-value are tests for the same sample means between Groups A and B.

Table 3 indicates that the difference is significant at the 5% level for ρ_i, θ_i, $\sigma_{\eta,i}$ and γ_i. Group A forecasters, whose trend inflation is higher than that of Group B forecasters, tend to see less persistence in cyclical component (lower ρ_i) as well as in stochastic volatility (lower θ_i), and smaller volatility in noise (lower $\sigma_{\eta,i}$ and lower γ_i).

Where the difference in these parameter values come from can be seen in the inflation forecast curves in Figure 6 which plots the average survey responses of Groups A and B against the corresponding quarters for the entire sample period (left-hand-side panel) and in 2017-2018 when the trend inflation hit the peak in Figure 1 (right-hand-side panel). In either case, the inflation forecast curve of Group A is located higher and its curvature is steeper than that of Group B. As explained above, trend components pin down the level of long-term inflation forecasts and transitory components determine the slope from the short-end to the long-end of forecasts (equation (6)). The combination of the near-zero cyclical component $c_{i,r}$ and the positive trend inflation $\tau_{i,t}$ implies that inflation forecasts $\hat{\pi}_{i,t,+k}$ are higher the longer the forecast period horizon (the larger k), thus the term structure of inflation forecasts is positively sloped. The smaller ρ_i for Group A forecasters is reflected in the steeper curve in Figure 6, and their larger $\tau_{i,t}$ is reflected in the higher curve.

The above heterogeneity can also be seen in disagreement about trend inflation, as graphed in the upper panel of Figure 7, which calculates the degree of disagreement by a dispersion

Figure 6: Quarterly Inflation Forecasts ($\hat{\pi}^q_{i,t,+k}$)

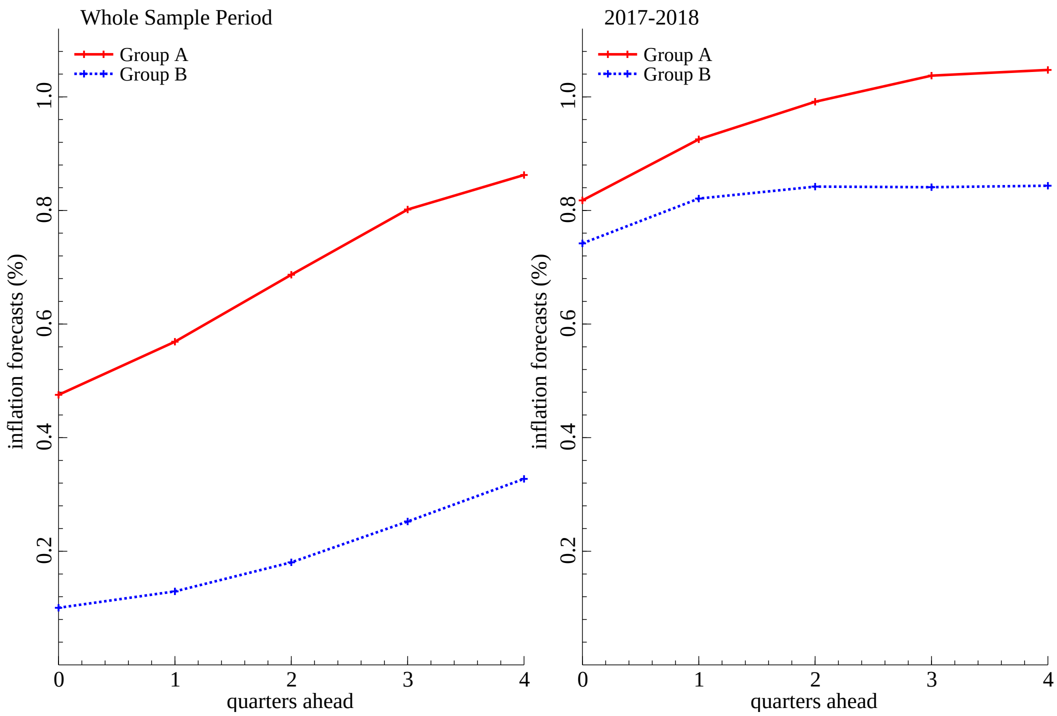
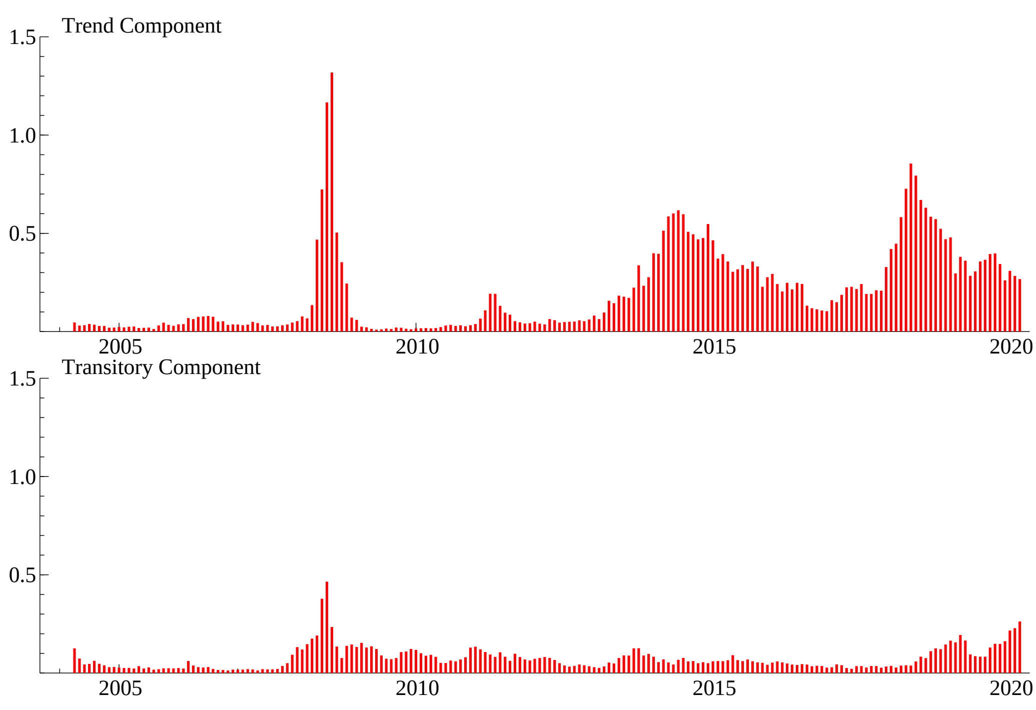


Figure 7: Disagreement



Note: Disagreement is calculated by the following dispersion measure: $d_t = \frac{1}{N_t - 1} \sum_i^{N_t} (x_{i,t} - x_{*,t})^2$ where $x_{i,t} = \tau_{i,t}$ or $c_{i,t}$ and $x_{*,t} = \tau_{*,t}$ or $c_{*,t}$ respectively.

measures:

$$d_t = \frac{1}{N_t - 1} \sum_{i}^{N_t} (\tau_{i,t} - \tau_{*,t})^2.$$

Estimated disagreement about trend inflation peaked three times, in 2008, 2014 and 2018. These timings coincide with episodes when both stochastic volatility and trend inflation surged. By contrast, there is a little increase in disagreement regarding the transitory components around 2014, though there were local peaks in 2008 and more recently in both 2019 and 2020 (bottom panel).

5 Discussion

5.1 Source of Heterogeneous Responses

The above findings can be restated that heterogeneous responses of forecasters, in particular the disagreement about trend inflation after 2013 (Figure 7), played a key role behind the surge in trend inflation observed in the mean inflation forecasts (Figure 1). Some forecasters, labelled as Group A above and who might be called "shifting trend believers", see less noise in the inflationary process, expect the impact of transitory inflationary shocks to wane more quickly, and are more flexible is adjusting their forecasts of trend inflation in response to new information. Another group of forecasters, labelled as Group B and who might be called "shifting trend skeptics", see more noise in the inflationary process, expect the impact of transitory inflationary shocks to wane more slowly, and are less flexible in adjusting their forecast of trend inflation in response to new information.

The fact that group A forecasters entered the survey relatively recently may provide another source of heterogeneous responses. Malmendier and Nagel (2016) note that young individuals with less history update their expectations more strongly than older individuals, particular in times of highly volatile inflation. More generally, Clements (2021) notes that forecasts of inflation of recent joiners to the survey they examine are found to be less accurate.

Differences in forecasters can also reflect strategic behavior on the part of forecasters who may have incentives to differentiate themselves well beyond the signals they observe (Laster et al. (1999), Ottaviani and Sørensen (2006)). Goldstein and Zilberfarb (2021) note that the strategic

Table 4: Affiliations of Forecasters

	Group A	Group B
Banks and Insurance Companies	3 (0.25)	15 (0.30)
Security Firms	6 (0.50)	23 (0.46)
Others (non-financial)	3 (0.25)	12 (0.24)
Total	12 (1.00)	50 (1.00)

Note: Number of forecasters. Figures in the parentheses are shares.

tendency of forecasters to "anti-herd" in this fashion is greater in times of higher inflation.

These forecasters might also be influenced by their affiliations. Table 4 indicates that "shifting trend believers" (Group A) are more affiliated with security firms while "shifting trend skeptics" (Group B) are more likely to be with banks and insurance companies. As these security firms deal with the volatile equity market, arguably, they might be more flexible to change their house views compared with rather conservative institutions like banks and insurance companies.[10] One caveat, however, is that given the limited number of institutions, we are unable to infer that the differences between Group A and B in sector affiliation are statistically significant at standard levels of significance.

5.2 Effectiveness of the 2% Inflation Target and UMP

How would these analyses of individual trend inflation lend themselves to the assessment of BOJ's enormous efforts to lift inflation? As stated above, the BOJ introduced the 2 percent inflation target in 2013M1 followed by a series of monetary easing measures. These include the Quantitative and Qualitative Monetary Easing (QQE) program in 2013M4, the adoption of Negative Interest Rates Policy (NIRP) in 2016M1 and Yield Curve Control (YCC) of 10 year JGB in 2016M9.

If, accompanied by the series of new measures, the new inflation target had been viewed as perfectly credible, we would not have observed an increase in disagreement on trend inflation (Figure 7). Rather, all individual trend inflation forecasts would have risen to 2 percent. More generally, Crowe (2010) and Ehrmann et al. (2012) show that the introduction of inflation targeting tends to reduce the dispersion of inflation forecasts, but the opposite happened in

[10] In the literature, Ito (1990) finds that forecasters in the yen/dollar exchange rate survey tend to be biased towards outcomes that favor their employers.

2013 in Japan. This likely reflects the difficulty in targeting inflation from below, where, as documented by Ehrmann (2015), under persistently low inflation below the central bank target, expectations tend to be unanchored, and forecasters disagree more.[11]

Indeed, our analysis shows that some forecasters (Group A) lifted their trend inflation to 2% (Figure 5) and this was a cause of rising disagreement. Though other forecasters (Group B) also raised their assessment of trend inflation, it was by much less.

The situation in the wake of the Bank of Japan's introduction of an inflationary targeting regime accompanied by large-scale monetary easing was that the glass was half full and half empty. The measures succeeded in raising the trend inflation of ESP forecasters, but not by enough to re-anchor inflationary expectations at the target. Many did not adjust their forecasts of trend inflation fully towards the 2 percent target. Our findings are consistent with Hattori et al. (2021), who show that ESP forecasters discounted the inflation forecasts made by the BOJ after the central bank raised its forecasts of the next fiscal year CPI inflation in line with the new 2 percent inflation target.

6 Conclusion

In this paper, we propose a noisy information model to extract trend inflation of individual forecasters. We find that the added noise term plays a crucial role and that there exists considerable heterogeneity among individual trend inflation forecasts that drives the dynamics of the mean trend inflation forecasts. Forecasters who see less noise in realised inflation tend to expect the impact of transitory inflationary shocks to wane more quickly, and are more flexible in adjusting their forecasts of trend inflation in response to new information. Their changing forecasts drove the increase in observed forecast differences during the recent introduction of inflation targeting and unprecedented monetary easing measures in Japan.

It is straightforward to apply our model to inflation forecasts made by professional forecasters in other countries. In principle, our model can also be applied to extract individual trend

[11] It is also possible that the announcement of regime change whereby qualitative new monetary policy measures were implemented could have been responsible for the increased disagreement, much as more controversial central bank communications can trigger a divergence in views among non-experts (Ehrmann and Wabitsch, 2022).

inflation of other agents such as households or corporations.[12] It would be interesting to see whether there is heterogeneity in individual trend inflation forecasts that follows similar patterns across these other groups, to shed further light on the formation of inflation expectations.

[12] Diamond et al. (2020) shows that there is heterogeneity in household inflation expectations across generations in Japan.

Appendix Selection Matrix

$\mathcal{S}$ is a 6×36 matrix and $\mathcal{S}^q$ and $\mathcal{S}^a$ are 1×14 and 1×23 vectors respectively.

$$\mathcal{S}^q = \left[\begin{array}{ccccccc} \frac{1}{3} & \frac{2}{3} & \frac{3}{3} & \cdots & \frac{3}{3} & \frac{2}{3} & \frac{1}{3} \end{array} \right] \text{ and } \mathcal{S}^a = \left[\begin{array}{ccccccc} \frac{1}{12} & \frac{2}{12} & \cdots & \frac{12}{12} & \cdots & \frac{2}{12} & \frac{1}{12} \end{array} \right].$$

$\mathcal{S}$ is defined for each month such that $\mathcal{S}^q$ and $\mathcal{S}^a$ are placed at the following elements of the matrix, otherwise zero.

	$\mathcal{S}^q$					$\mathcal{S}^a$
M1	(1,4)	(2,7)	(3,10)	(4,13)	(5,16)	(6,7)
M2	(1,6)	(2,9)	(3,12)	(4,15)	(5,18)	(6,6)
M3	(1,5)	(2,8)	(3,11)	(4,14)	(5,17)	(6,5)
M4	(1,4)	(2,7)	(3,10)	(4,13)	(5,16)	(6,4)
M5	(1,6)	(2,9)	(3,12)	(4,15)	(5,18)	(6,3)
M6	(1,5)	(2,8)	(3,11)	(4,14)	(5,17)	(6,14)
M7	(1,4)	(2,7)	(3,10)	(4,13)	(5,16)	(6,13)
M8	(1,6)	(2,9)	(3,12)	(4,15)	(5,18)	(6,12)
M9	(1,5)	(2,8)	(3,11)	(4,14)	(5,17)	(6,11)
M10	(1,4)	(2,7)	(3,10)	(4,13)	(5,16)	(6,10)
M11	(1,6)	(2,9)	(3,12)	(4,15)	(5,18)	(6,9)
M12	(1,5)	(2,8)	(3,11)	(4,14)	(5,17)	(6,8)

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